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Assessing response of sediment load variation to climate change and human activities with six different approaches

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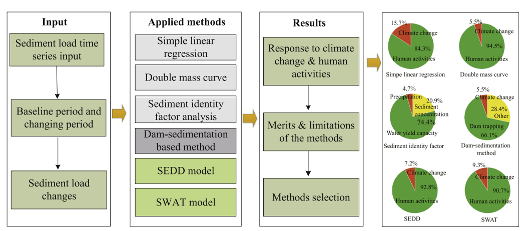
HIGHLIGHTS

- We assessed the response of sediment load to climate change and human activities with six methods.
- Five methods produced similar estimates except for the linear regression.
- Sediment load exhibited 70.5% reduction, but inconsistent with annual sediment yield.
- Human activities played a dominant role, accounting for 93.6 ± 4.1% sediment load reduction.

GRAPHICAL ABSTRACT



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ABSTRACT

Understanding the relative contributions of climate change and human activities to variations in sediment load is of great importance for regional soil, and river basin management. Considerable studies have investigated spatial-temporal variation of sediment load within the Loess Plateau; however, contradictory findings exist among methods used. This study systematically reviewed six quantitative methods: simple linear regression, double mass curve, sediment identity factor analysis, dam-sedimentation based method, the Sediment Delivery Distributed (SEDD) model, and the Soil Water Assessment Tool (SWAT) model. The calculation procedures and merits for each method were systematically explained. A case study in the Huangfuchuan watershed on the northern Loess Plateau has been undertaken. The results showed that sediment load had been reduced by 70.5% during the changing period from 1990 to 2012 compared to that of the baseline period from 1955 to 1989. Human activities accounted for an average of 93.6 ± 4.1% of the total decline in sediment load, whereas climate change contributed 6.4 ± 4.1%. Five methods produced similar estimates, but the linear regression yielded relatively different results. The results of this study provide a good reference for assessing the effects of climate change and human activities on sediment load variation by using different methods.

1. Introduction

Sediment transport plays a critical role in global biological and geochemical cycles of the terrestrial ecosystem (Keesstra et al., 2012; Syvitski et al., 2009). Recent observed evidence from many rivers indicate that sediment load have been substantially disturbed throughout

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the world owning to climate change, land use change, tillage, mining, dam construction, soil and water conservation and other human activities (Boix-Fayos et al., 2007; Fu et al., 2017; Kondolf et al., 2014; Syvitski et al., 2009). Assessment the relative role of climate change and human activities on sediment load can provide scientific insight to understand the complex hydrological response to its driving factors (Kondolf et al., 2014; Ma et al., 2014), as well to develop strategies for river basin management and sustainable agricultural production.

During the past decades, numerous studies have attempted to evaluate the relative roles of climate change and human activities in changes of riverine sediment load (Gao et al., 2017a; Shi and Wang, 2015; Wang et al., 2012). Among these studies, several types of methods were regularly employed, including the empirical regression method, sediment identity factor method, and soil erosion models. Empirical regression method (such as linear regression and double mass curve) is usually based on the relationship between sediment load and precipitation (Bhattarai and Dutta, 2008; Miao et al., 2011; Tang et al., 2013; Wang et al., 2012; Ward and Jackson, 2004). Compared with empirical methods, soil erosion models include relative complex physical mechanisms, and can assess the effects of climate change and human activities on sediment load over different temporal scales (de Vente et al., 2013). The empirical soil erosion models (i.e. RUSLE, WATEM/SEDEM and SEDD) have been widely applied with different land use scenarios at various spatial and temporal scales (Boix-Fayos et al., 2008; Fu et al., 2011; Zhao et al., 2017). The physics-based model, Soil and Water Assessment Tool (SWAT) has great applicability for predicting the impact of land management practices on sediment transport in large river basins, and has been tested in various countries (Arnold et al., 2012; Li et al., 2017; Ouyang et al., 2018; Pandey et al., 2016; Vigiak et al., 2017).

The sediment identity factor decomposition method is originally analogous to the Kaya Identity in economics (Kauppi et al., 2006; Raupach et al., 2007). Wang et al. (2017) applied this method to diagnose the contributions of precipitation, water yield capacity and sediment concentration to the relative change of sediment load in the Yellow River basin. Another method was conceptually based on the statistics in soil conservation measures, which utilized the total area of conservation measures and their trapping efficiencies to assess the effects on sediment load reduction (Ward and Jackson, 2004). Trapping efficiencies for each type of conservation measures were observed by using soil erosion plots or estimated through field survey.

The Loess Plateau has long been suffering from severe soil erosion with erosion-prone area of about 472,000 km^2. Serious soil erosion has led to unsustainable land use management, and threatened agriculture production and ecological system (Fu et al., 2011). In recent years, a series of soil and water conservation measures have been extensively implemented (Fu et al., 2017; Liu et al., 2014; Xin et al., 2015; Yao et al., 2011). These measures (e.g. terracing, afforestation and re-establishing natural vegetation cover) have considerably reduced sediment load from hillslopes to the main river channels. A significant reduction of sediment load ($p < 0.05$) in the Yellow River has been detected by a large number of studies, and the causes of sediment load changes have also been investigated with different approaches (Gao et al., 2017b; Liu et al., 2014; Xu, 2008; Yao et al., 2011). However, it is unknown that whether these methods can produce consistent results in a specific watershed; and the results might be applicable to other watersheds within the Loess Plateau or not. Because of all of the above, we selected the Huangfuchuan watershed as the case study for assessing the response of sediment load reduction to climate change and human activities with different methods. Our results not only quantify the impacts of climate change and human activities on changes in sediment load in the Huangfuchuan watershed, but provide a good reference for soil and water conservation in the Loess Plateau. The novelties and objectives of this study are: (1) to quantify the impacts of climate variability and human activities on variation of sediment load with six widely used methods. (2) to identify the applicability of the different methods, and the respective merits and limitations of the methods in detail.

2. Material and methods

2.1. Study area

This study was undertaken in the Huangfuchuan watershed in the northern Loess Plateau, China. The watershed covers an area of 3246 km^2, and is a first-order tributary of the Yellow River. The river originates from southern Inner Mongolia, drains to the Loess Plateau, and discharges into the Yellow River in northern Shaanxi Province (Fig. 1). The watershed has a typical semi-arid continental climate, with average annual rainfall of 380 mm and mean annual temperature of 7.5 °C. Rainfall is strongly seasonal, with 76% falling between June and September. Concentrated rainfall resulted in severe soil erosion, leading to large amount of sediment discharged into Yellow River. As addressed by Wei et al. (2017) and Zhao et al. (2015a), soil erosion was very serious, with average annual soil erosion rate >120 t/ha.

The catchment is characterized by three main types of soil: silt loess, sand, and deeply weathered coarse-grained sandstone (locally name Pisha stone). The dominant vegetation in the catchment is grassland, sparsely distributed on the loess soil in the gentle hill slopes. The badland Pisha sandstone has very sparse or no vegetation cover, and is the dominant sediment source, contributing >70% of coarse sediment in the watershed (Zhao et al., 2015a).

2.2. Data sets

Daily precipitation at 12 stations was obtained from the Hydrology Bureau of the Yellow River Water Resources Commission. Among these stations, seven started observations since 1950s, and the other five were established in 1976. Observed daily

sediment load data at Huangfu station is available from 1950s to 2012, which is collected from the "Hydrological Yearbook of the People's Republic of China, provided by the Yellow River Water Conservancy Committee.

The digital elevation map (DEM) with 30 m grid size was derived from topography data (1:100000), which was provided by the Geomatics Center of Shaanxi Province. The land use/cover map for the 1980s was extracted from satellite images with 30 m resolution, which originally obtained from Enhanced Thematic Mapper (ETM) sensor (http:// http://glcfapp.umiacs.umd.edu:8080/esdi/index.jsp). The images were interpreted by using the unsupervised classification method. The soil map was derived from the field survey, and provided by the Institute of Soil and Water Conservation, Chinese Academy of Sciences (Zhao et al., 2017). The data quality and results have been checked out according to field campaign before their release.

Check dam has become one of the most popular soil and water conservation measures on the Loess Plateau (Li et al., 2017; Zhao et al., 2017). The sedimentation behind the check-dam recorded detailed information of soil erosion in its upstream area. Recently, an increasing number of studies attempted to deduce sediment yield through sedimentation behind the check dams, not only on the Loess Plateau (Li et al., 2016; Wei et al., 2017), but also in other erodible regions throughout the world (Boix-Fayos et al., 2007; Romero-Díaz et al., 2007). In this study, sediment yield data behind six check dams were collected in the spring of 2014 and 2015. Fig. 1b shows their locations. An example of sediment profile and sediment yield is shown in Fig. 2. The details of sedimentation sampling procedure are available in Wei et al. (2017, 2018) and Zhao et al. (2015a).

2.3. Methodologies

2.3.1. Identification of baseline and changing periods

To assess the hydrological response to climate change and human activities, most studies divided the hydrological time series into two or more periods (Ma et al., 2014; Shi and Wang, 2015). The first period represents the baseline or referenced period, when very limited or no

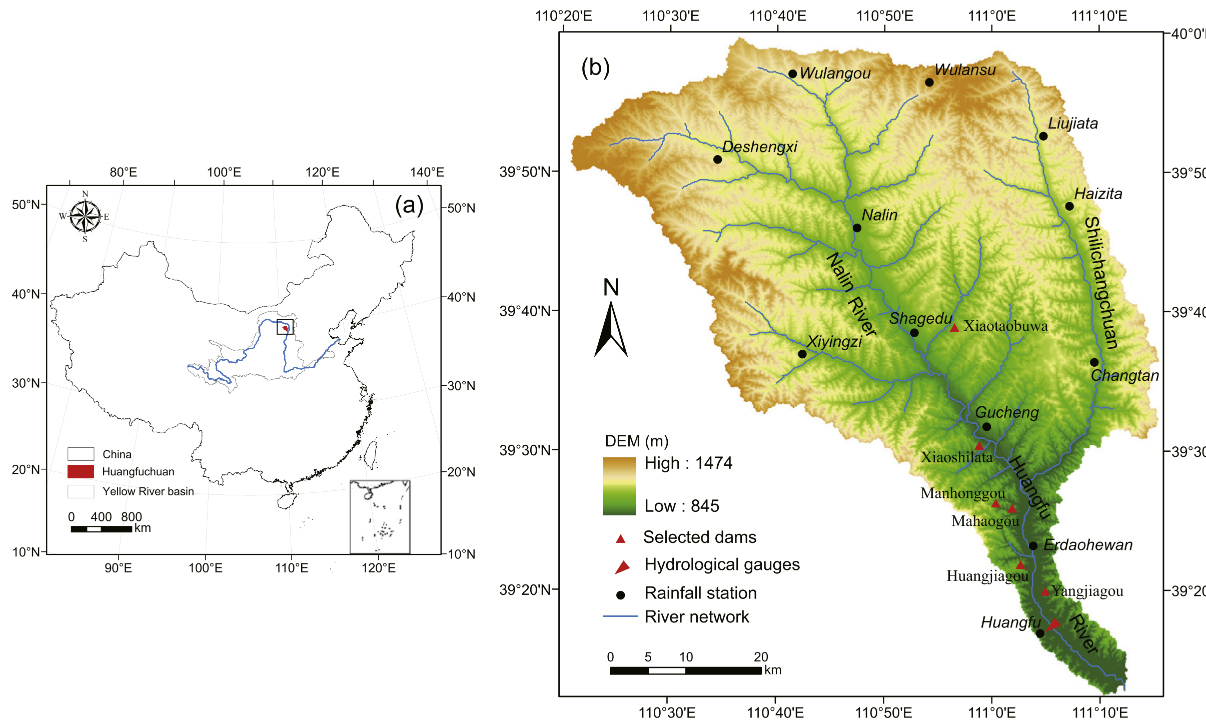

Fig. 1. Location of the Huangfuchuan catchment. (a) Inset map showing the location of the study area; (b) map of the Huangfuchuan catchment showing the locations of rainfall stations, hydrological gauge and check dams.

significant human activities occurred; and the second is the changing period, when the watershed experienced significant changes in land use, dams, and afforestation/deforestation. The abrupt change point method is an efficient and scientific way providing reliable results to identify the baseline period and changing period. Many studies applied different "changing point" separation methods to analyze the statistical features of the long-term hydrological time series (Tang et al., 2013; Zhao et al., 2015b). Commonly used methods for identifying the abrupt change point include the sequential Mann-Kendall test, double mass curve, Pettitt test and accumulative anomaly method et al. (Kendall, 1975; Mann, 1945; Wang et al., 2012; Wu et al., 2017). Thus, this study applied accumulative anomaly method to divide the whole sediment load time series into a baseline period and a changing period.

2.3.2. Framework to assess the impacts of climate change and human activities on sediment load variation

Fig. 3 shows the framework of this study to assess the effects of climate variability or human activities on sediment load. To evaluate the effects of climate change and human activities, sediment load time series were divided into two parts, i.e. baseline period (referenced) and

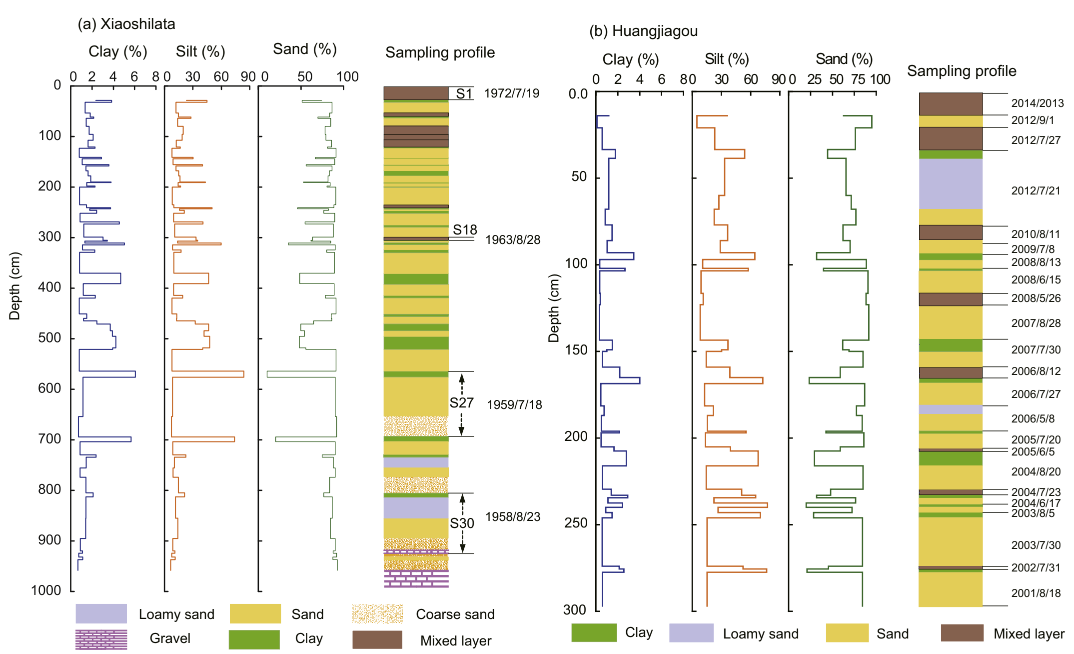

Fig. 2. Sampling profile examples of sedimentation behind the check dams. (a) The sedimentation profile in Xiaoshilata watershed and (b) the sedimentation profile in Huangjiagou watersheds.

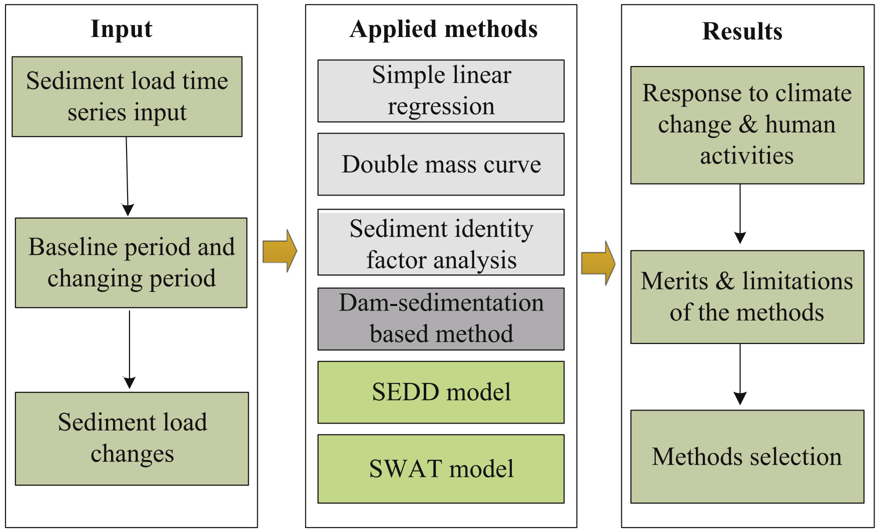

Fig. 3. Flowchart of the method to assess the impacts of climate change and human activities on sediment load variation.

changing period. And a change in average annual sediment load can be calculated as:

$$\Delta\overline{S} = \overline{S}_{ref} - \overline{S}_{change} \tag{1}$$

where $\Delta\overline{S}$ is the change in annual average sediment load, $\overline{S}_{ref}$ and $\overline{S}_{change}$ are the mean annual sediment load within the baseline/referenced and changing periods, respectively. For a given watershed, the changes in sediment load can be attributed to climate change and human activities:

$$\Delta\overline{S} = \Delta\overline{S}^{c} + \Delta\overline{S}^{h} \tag{2}$$

where $\Delta\overline{S}^{c}$ and $\Delta\overline{S}^{h}$ are the contribution of climate change and human activities to sediment load.

2.3.2.1. Simple linear regression. Simple linear regression is a statistical method that does not consider the physical hydrological processes (Wang et al., 2012). The relationship between annual sediment load (S_{ref}) and rainfall (P_{ref}) in the baseline period can be expressed as:

$$S_{ref} = a \cdot P_{ref} + b \tag{3}$$

where a denotes the changing rate of sediment load related to the changes of precipitation, and b is the intercept. By extending the regression equation between sediment load and precipitation (P_{change}) in the changing period, the sediment load (S_{fit}) can be reconstructed as:

$$S_{fit} = a \cdot P_{change} + b \tag{4}$$

And the contribution to sediment load variations by human activities and precipitation can be estimated as:

$$\Delta S^{h} = \overline{S}_{fit} - \overline{S}_{change} \tag{5}$$

$$\Delta S^{c} = \overline{S}_{ref} - \overline{S}_{fit} \tag{6}$$

where $\overline{S}_{fit}$ is the estimated annual mean sediment load from S_{fit}, $\overline{S}_{ref}$ and $\overline{S}_{change}$ are the same as those in Eq. (1).

2.3.2.2. Double mass curve. The double mass curve method is a very simple, but widely used method for analyzing the consistency between hydrological and climatic variables (Gao et al., 2017b; Xin et al., 2015). The approach is conceptually based on the fact that the two variables are high linearly correlated. Taking relationship between the sediment load $S_i(i=1,2,3\cdots N)$ and precipitation $P_i(i=1,2,3\cdots N)$ as an example, the changing point occurs at S_M, where $1<M<N$, and the whole series can be divided into the baseline and changing period. In the baseline period, the relationship between the cumulative sediment load and cumulative rainfall can be estimated as:

$$\sum_{i=1}^{M} S_i = a_1 \sum_{i=1}^{M} P_i - b_1 \quad i = 1,2,3,\ldots,M \tag{7}$$

And for the changing period:

$$\sum_{i=M+1}^{N} S_i = a_2 \sum_{i=M+1}^{N} P_i - b_2 \qquad i = M+1, M+2, \ldots, N \tag{8}$$

where the parameters a_1 and a_2 are the changing rates of accumulated sediment load with changes in accumulated precipitation, b_1 and b_2 are the intercept values. Afterwards, the mean annual sediment load in the changing period can be reconstructed as:

$$\overline{S}_{fit} = \frac{a_1 \sum_{i=1}^{M} P_i - b_1}{N-M} \qquad i = M+1, M+2, \ldots, N \tag{9}$$

The contributions from climate change and human activities to variation in sediment load can be determined by Eqs. (5) and (6).

2.3.2.3. Sediment identify factor analysis. The sediment identify factor analysis method can be used to diagnose the changes in river sediment load to different drivers (Wang et al., 2017). Sediment load was expressed as a product of three driving factors:

$$S = P \cdot \left(\frac{Q}{P}\right) \cdot \left(\frac{S}{Q}\right) = P \cdot R \cdot Sc \tag{10}$$

where S is sediment load, P is precipitation, Q is runoff and R is water yield capacity (the ratio of river discharge to precipitation) and Sc is sediment concentration.

The above equation can be decomposed as:

$$\frac{dS/dt}{S} = \frac{dPRSc/dt}{PRSc} = \frac{dP/dt}{P} + \frac{dR/dt}{R} + \frac{dSc/dt}{Sc} \tag{11}$$

And the changes of sediment load can be attributed to changes in precipitation, runoff and sediment concentration.

$$\Delta S = \Delta S^{P} + \Delta S^{R} + \Delta S^{Sc} \tag{12}$$

The relative contribution of each factor was determined as the ratio of its proportional growth rate to the proportional changing rate of ΔS in the same period.

2.3.2.4. Dam-sedimentation based method. The dam-sedimentation based method can be used to quantify the effects of dams/reservoirs on sediment load changes on the Loess Plateau (Jiao et al., 2003; Wei et al., 2017). The method firstly uses the double mass curve to assess the contributions of climate change and human activities to the changes in sediment load. Then, average annual sediment yield from different check dams is estimated from field sampling (Fig. 2). The total amount of sediment trapped by check dams/reservoirs in the catchment can be calculated as:

$$\Delta S^{dam} = M \cdot A \cdot T \cdot TE \tag{13}$$

where M is basin-averaged sediment yield (t/ha/year), which is an average value of annual sediment yield from different check dams. A is the controlled area by check dams (ha), T is the check dam operation period (year), and TE is the sediment trapping efficiency (dimensionless). For small dams without any sluicing gate, TE equals to 1.0, suggesting all the sediment eroded from upstream are trapped behind the check dams. For medium/large check dams with sluicing gate, an average of 0.85 is selected based on previous studies (Wei et al., 2017). And then, the contribution from other factors (vegetation restoration, terracing, water extraction etc.) can be estimated as:

$$\Delta S^{other} = \Delta S^{h} - \Delta S^{dam} \tag{14}$$

2.3.2.5. The SEDD model. An increasing number of studies attempted to use soil erosion models to quantify the effects of climate change and human activities on variation in sediment load. In general, two types of models, i.e. empirical model and physically based model, are commonly used for investigation. Empirical model (such as USLE and SEDD model) (Ferro and Minacapilli, 1995; Wischmeier and Smith, 1978) requires less input data with relative simple model framework, and are easier to calibrate, whereas physically based models (e.g. EUROSEM model, SWAT model (Arnold et al., 1998; Morgan et al., 1992)) requiring more input data, can simulate more complex hydrological and erosion processes at various spatial and temporal scales (Pandey et al., 2016).

The Sediment Delivery Distributed (SEDD) model is an empirical soil erosion model based on the concept of Revised Universal Soil Loess Equation (RUSLE) model (Ferro and Minacapilli, 1995; Ferro and Porto, 2000). $\mathrm{TE} = 1 - \frac{1}{1+0.0021\mathrm{D}\frac{\mathrm{V}}{\mathrm{W}}}$The model discretizes a watershed into morphological units (sub-watersheds) and determines sediment deliver ratio (SDR) for each unit (Ferro and Porto, 2000). According to Ferro and Minacapilli (1995) and Taguas et al. (2011), the sediment delivery ratio can be estimated as:

$$SDR_{w} = \sum_{j=1}^{N} exp(-\beta t_{j}) l_{j}^{0.5} s_{j}^{2} a_{j} / \sum_{j=1}^{N} l_{j}^{0.5} s_{j}^{2} a_{j} \tag{15}$$

where N is total number of cells over the specific watershed, β is basin-specific parameter, mainly depending on regional morphological data, t_j denotes the travel time (hour) for cell j to the nearest river channel along the flow path, l_j is the length of cell along the flow path, s_j is the slope of the cell, and a_j is the area of the cell.

The sediment yielded in each unit is calculated as:

$$S_{w} = R_{USLE} \cdot K_{USLE} \cdot LS_{USLE} \cdot C_{USLE} \cdot P_{USLE} \cdot SDR_{w} \cdot A_{w} \tag{16}$$

where R_{USLE}, K_{USLE}, C_{USLE}, P_{USLE}, LS_{USLE} are the rainfall erosivity factor, soil erodibility factor, cover and management factor, support practice factor and topographic factor, respectively. A_w denotes the unit area (ha). After the model was well calibrated, sediment load is simulated with the same set of parameters in the changing period without considering any human impacts. Differences in simulated sediment load before and after the change point are attributable to climate change, and can be calculated as:

$$\Delta \overline{S}^{h} = \overline{S}_{change}^{sim} - \overline{S}_{change} \tag{17}$$

$$\Delta \overline{S}^{c} = \overline{S}_{ref} - \overline{S}_{change}^{sim} \tag{18}$$

where $\overline{S}_{change}^{sim}$ is simulated average annual sediment load within changing period.

2.3.2.6. The SWAT model. The SWAT model is a distributed watershed hydrological model based on physical mechanism (Arnold et al., 1998, 2012), which has thoroughly applied to investigate runoff and sediment transport at different temporal scales (Li et al., 2017; Wilson and Weng, 2011; Wu et al., 2017; Zuo et al., 2016). The Modified Universal Soil Loss Equation (MUSLE), a function of runoff factor, was used to estimate sediment yield on a given day:

$$Sed = 11.8 \cdot \left(Q_{surf} \cdot q_{peak} \cdot A_{hru}\right)^{0.56} \cdot K_{USLE} \cdot C_{USLE} \cdot P_{USLE} \cdot LS_{USLE} \cdot CFRG \tag{19}$$

where Sed is the sediment yield (t), Q_{surf} is the surface runoff volume (mm/ha), q_{peak} is peak A_{hru} runoff (m^3/s), Area is the area of hydrological response units (HRU, ha), K_{USLE}, C_{USLE}, P_{USLE}, LS_{USLE} are the same with Eq. (16), and $CFRG$ is coarse fragment factor. Similar to the SEDD model procedure, the differences in simulated sediment load before and after changing point are predicted using the calibrated model. The contributions of climate change and human activities to the changes in sediment load can be estimated by Eqs (17) and (18), respectively.

2.3.3. Sensitivity analysis

The empirical SEDD model has very limited parameters to calibrate, thus, only the cover management factor (C), soil erodibility factor (K), support practice factor (P) and the basin-specific parameter β are considered for parameter sensitivity analysis. A local sensitivity analysis (One-At-a-Time, OAT) method was employed to calculate the sensitivity as the ratio between the relative changes of model output and the relative change of a parameter. As suggested by Lenhart et al. (2002), each parameter value was increased or decreased by a fixed percentage of the calibrated/validated range, while all the other parameters remained fixed values. The differences in model output between test simulations with increasing/decreasing parameters and the base simulation were used to determine the parameters sensitivity (Huang et al., 2016).

The SWAT model was initially warmed-up within the period of 1976–1977, and 6 years of continuous monthly sediment load was used for both calibration (1978–1983) and validation (1984–1989). The parameters were firstly initialized in a reasonable range from the literature (Li et al., 2017; Zuo et al., 2016), and then adjusted through the SWAT-CUP tool until model simulation satisfactorily matched the observed values. The LH-OAT analysis method (van Griensven and Meixner, 2006) was employed for parameters sensitivity analysis.

3. Results

3.1. Sediment load changes

Fig. 4a shows temporal trend of annual sediment load at Huangfu station. A five-year smoothing window is applied to approximate the annual sediment load changes, which suggested large fluctuations from 1955 to 1989. The simple linear trend analysis between 1990 and 2012 indicates that annual sediment load presents significant downward trend within the confidence level of 95%. An average decreasing rate of 3.79 t/ha/a is detected. We found low R^2 of 0.20 and high standard error of 0.005 for the slope, suggesting high variances in annual sediment load.

The cumulative anomaly of annual sediment load is plotted in Fig. 4b. Three change points in 1979, 1989 and 1998 are examined from the cumulative anomaly curve, which exhibits an upward trend in sediment load during the period before 1979, a fluctuated period between 1980 and 1989, and then a decreasing trend within the period after 1990. A particularly significant downward trend ($p < 0.05$) was examined after 1999, which was possibly caused by the "Grain for Green" project operation. Annual average sediment load decreased from 60 Mt. during 1955–1979 to 8.7 Mt. within 1999–2012, which is 85.5% lower than the average annual for 1955–1979 and 80.0% lower for 1980–1989.

3.2. Sediment load variation response to climate change and human activities

To assess the effects of climate change and human activities on sediment load changes, the annual sediment load time series had to be divided into different periods (baseline and changing period). Since the cumulative anomaly curve showed three change points, we also applied the double mass curve method to the annual sediment load time series. A consistent transition year in 1989 was determined by both methods (Figs. 4b and 5b). Thus, a baseline period from 1955 to 1989 was assumed to be the period without intensive human influences on hydrological process, and the changing period was 1990–2012, which was highly affected by human activities.

3.2.1. Simple linear regression

After determining the baseline and changing periods, we used simple linear regression to assess the relative contributions of climate change and human activities to changes in sediment load in the Huangfuchuan watershed (Fig. 5a). The linear relationship between sediment load and precipitation in the baseline period was estimated. And then the sediment load within the changing period was reconstructed by using annual precipitation and the Eq. (4). The results suggested that human activities played a dominant role in sediment load changes in the Huangfuchuan catchment, and accounted for 84.3% of the total reduction (Fig. 6a). The remaining 15.7% was attributed to climate change.

3.2.2. Double mass curve

The relationship between sediment load and corresponding precipitation affords a useful means in assessing the effects of climate change and human activities on sediment load changes. Linear regression was conducted between accumulative sediment load and accumulative precipitation in the baseline period (Fig. 5b). The correlation equation was then used in subsequent reconstructing sediment load in the changing period (1990–2012).

Similarly, double mass curve indicated that human activities were the main driving forces to the significant decrease in sediment load, accounting for 94.5% of the total reduction, whereas climate change accounted for 5.5% of the total reduction (Fig. 6b).

3.2.3. Sediment identify factor analysis

The sediment identify factor decomposition method, unlike the above mentioned methods, took into account of different variables in a quantitative way. Three factors (i.e. precipitation, water yield capacity and sediment concentration) were considered as the dominant driving forces influencing changes in sediment load.

Fig. 6c shows the relative contributions of precipitation, the water yield capacity and changes in sediment concentration to sediment load decrease during the changing period. The sediment identity factor method suggested that precipitation, runoff yield capacity, and sediment concentration trends contributed an average of 4.7%, 74.4%, and 20.9%, respectively, to the sediment load reduction.

3.2.4. Dam-sedimentation based method

The regional averaged annual sediment yield was obtained from the reconstructed sedimentation records. As shown in Fig. 7, annual sediment yield varied greatly in the Huangfuchuan catchment, with an average annual value of 149.15 t/ha. The maximum annual sediment yield was 410.58 t/ha/a in 1989, which resulted from several extremely heavy storm events. No sediment yield was detected in 1980 and 2011 respectively, since no erosive rainfall events occurred in these years. The regional averaged sediment yields were 111.9 t/ha/a during 1958–1979, 167.8 t/ha/a within 1980–1998 and 139.5 t/ha/a between 1999 and 2012. The variation is inconsistent with that of annual sediment load at Huangfu station.

According to the average annual sediment yield and dam controlled area, the total sediment trapped by the check dams was estimated. Fig. 6d showed the relative contribution of rainfall variation, dams trapping and other factors. Compared to the baseline period, sediment load reduced approximately 70.5%, with 5.5% of this decline being explained by precipitation, 66.1% trapped by check dams, and the remaining 28.4% being attributable to other factors such as afforestation, sand dredging etc.

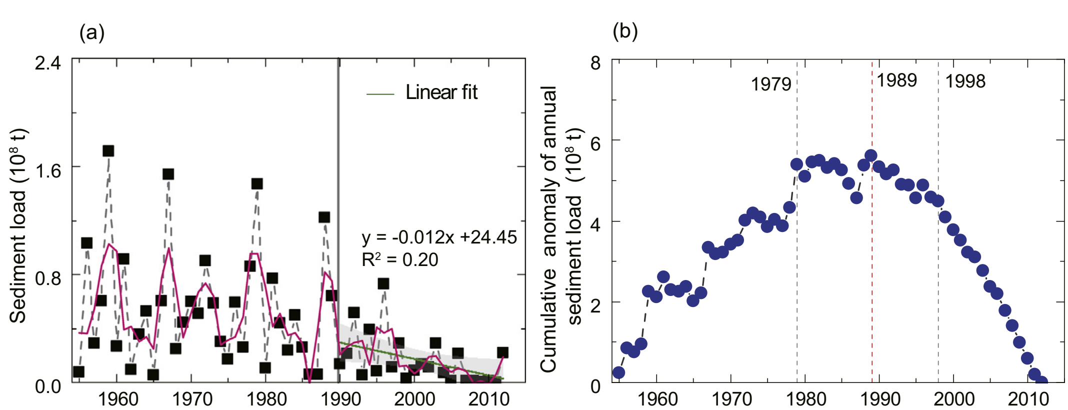

Fig. 4. Temporal changes in sediment load at Huangfu station (a) linear trends analysis of sediment load; (b) cumulative abnormal of annual sediment load.

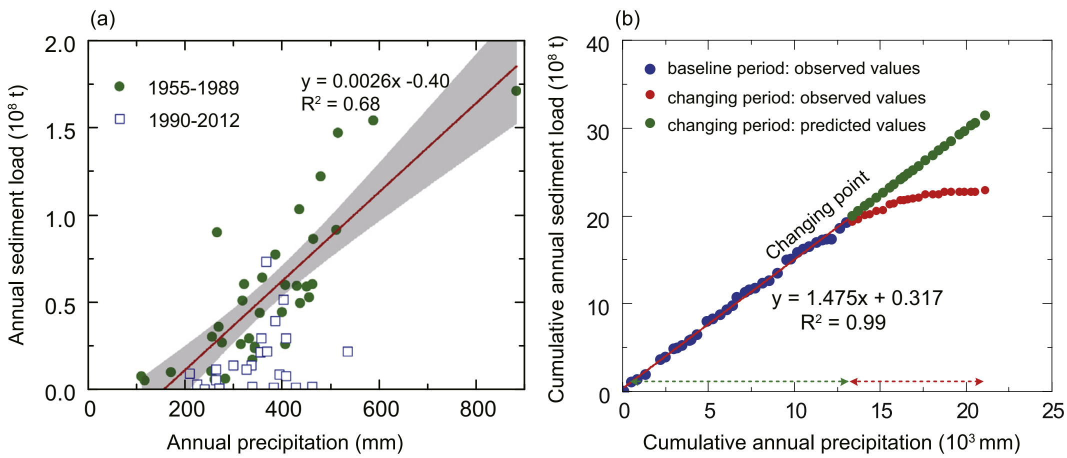

Fig. 5. Linear regression and double mass curve analysis of sediment load.

3.2.5. The SEDD model

In the SEDD model, we used long-term daily rainfall time series (1976–2012) to estimate rainfall erosivity factor. The land use, soil map and digital elevation model data were used as model input. The SEDD model was firstly verified by using the observed annual sediment load at Huangfu station during 1978–1989. Fig. 8a showed the relationship between observed and simulated sediment load at Huangfu station. It can be clearly seen that the points mostly distributed around the 1:1 line, suggesting a good agreement between observed and simulated sediment load. The simulated average annual sediment yield was 194.72 t/ha/a, approximate 13.1% higher than the observed value.

After model verification, the SEDD model was applied to the changing period for sediment load estimation. An average of 52.3 Mt/a sediment load was simulated, which was much higher (308.6%) than the observations (16.25 Mt/a) (Fig. 8b). The differences between simulated and observed sediment load was attributed to human activities. Fig. 6e showed the sediment load variation response to climate change and human activities, which exhibited inconsistent results with those from simple linear regression, but close to the double mass curve method. Accordingly, human activities accounted for 92.8% of sediment load reduction, and the remaining 7.2% was attributable to the changes in precipitation.

3.2.6. SWAT modeling

The SWAT model was setup with long-term daily climatic variables within the period of 1976–2012 to estimate the effects of climate change and human activities on changes in sediment load in the Huangfuchuan catchment. The model was established and parameterized with land use, DEM and soil maps, which were used for discretizing research area into different HRUs (hydrologic response units).

Fig. 9 shows the comparison between observed and simulated monthly sediment load at Huangfu station within the calibration period (1978–1983) and validation period (1984–1989). The relative high determination coefficient (R^2) and Nash-Sutcliffe coefficient (NS) in both calibration ($R^2 = 0.82$, NS = 0.80) and validation periods ($R^2 = 0.77$, NS = 0.78) suggested that the model provides good agreement

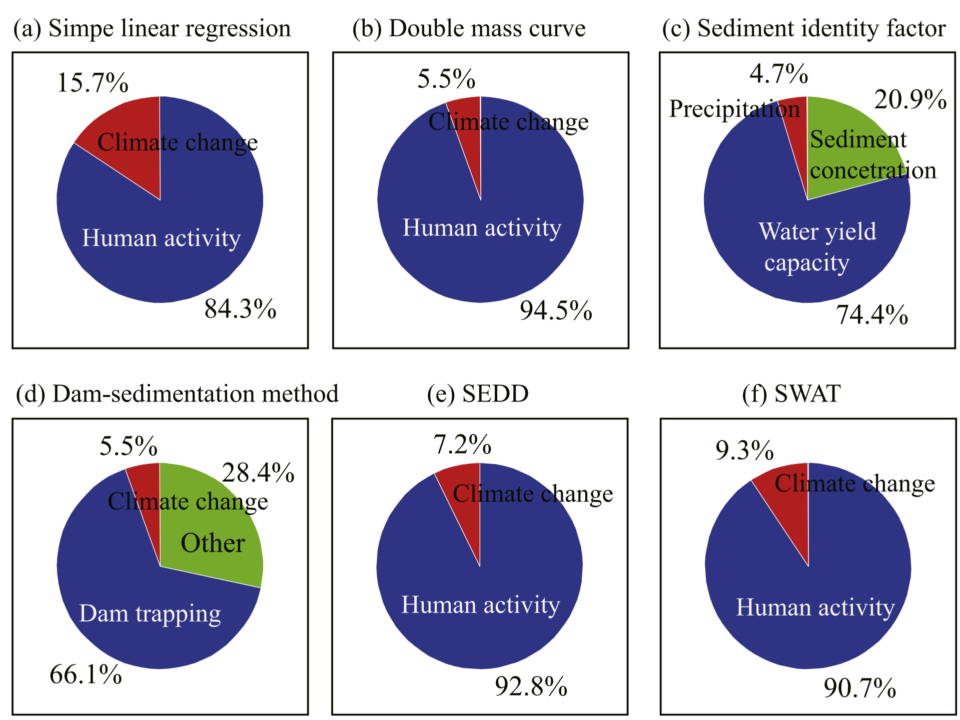

Fig. 6. Relative contributions of climate change and human activities to sediment load variation.

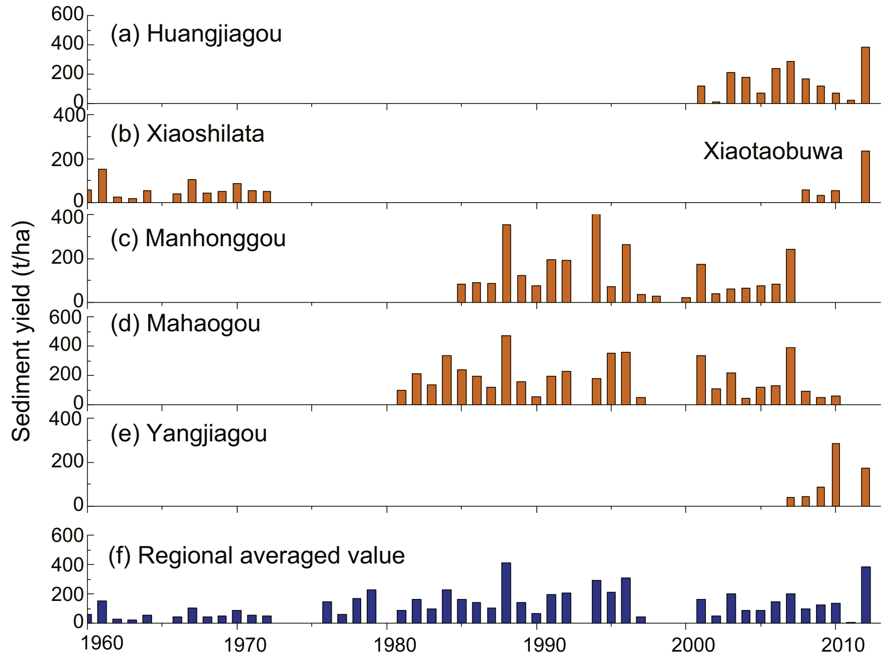

Fig. 7. Temporal variation of sediment yields estimated from sedimentation in six different dam-controlled watersheds (see Fig. 1b) (a) Huangjiagou, (b) Xiaoshilata and Xiaotaobuwa, (c) Manhonggou, (d) Mahaogou, (e) Yangjiagou, (f) Regional averaged sediment yield.

between the monthly observed and the simulated sediment load. Therefore, it can be inferred that the modeling results was satisfactory for model verification according to the model performance criteria addressed by Santhi et al. (2001). However, some sediment load peaks were underestimated (Fig. 9a). This may be caused by the calculation procedure of sediment transport in SWAT model, which has weakness to represent the characteristics of intensive storms yielding flash flood and hyper-concentrated sediment flow.

Within the changing period, the SWAT model produced average annual sediment of 55.0 Mt/a sediment load. A large differences between observed (16.25 Mt./a) and simulated sediment load existed, which can be attributed to intensive human activities. Based on Eqs. (17) and (18), human activities contributed 90.8% to the sediment load reduction during the period of 1990–2012, and the remaining is attributed to climate change (Fig. 6f).

3.3. Sensitivity analysis

Based on the criteria defined by Lenhart et al. (2002), two parameters (cover management factor and soil erodibility factor) have high sensitivity. The annual sediment load is particularly sensitive to cover management (*C* factor), which represents the effects of land use change on soil erosion and sediment transport. A 10% change in parameter *C* results in approximately 8% sediment load changes. Comparably, the basin-specific parameter β used for SDR estimation, is medium sensitive. Due to limited area of terraces and other conservation practices, the model output is not sensitive to the support practice (*P* factor). Previous studies from Borrelli et al. (2017) and Estrada-Carmona et al. (2017) indicated that the RUSLE predictions are most sensitive to the *C* factor and topography (*LS* factor). Given the topography did not vary greatly; our study did not assess the sensitivity of LS factor. As

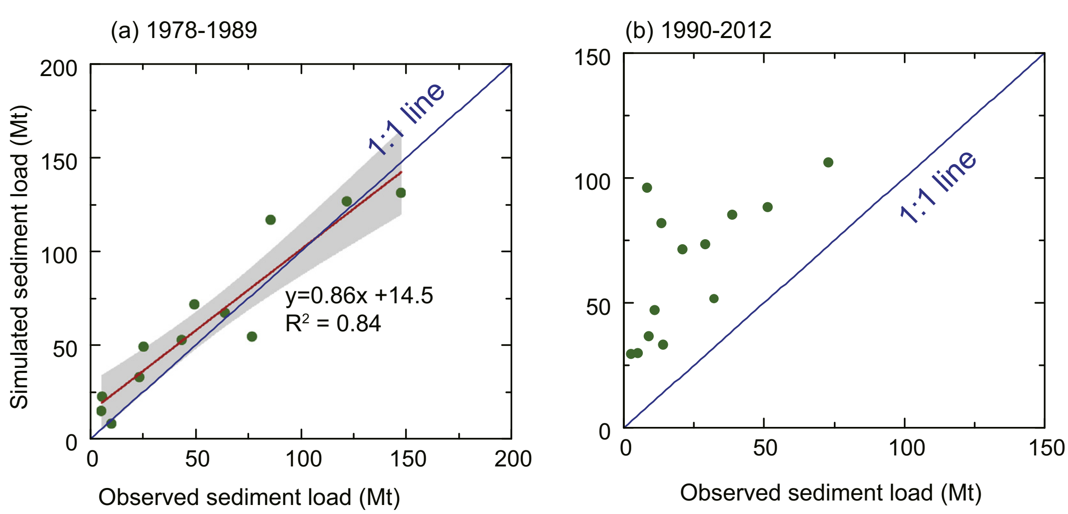

Fig. 8. The relationship between observed and simulated sediment load at Huangfu station (a) the SEDD model verification using sediment load observation from 1978 to 1989; (b) observed and simulated annual sediment load from 1990 to 2012.

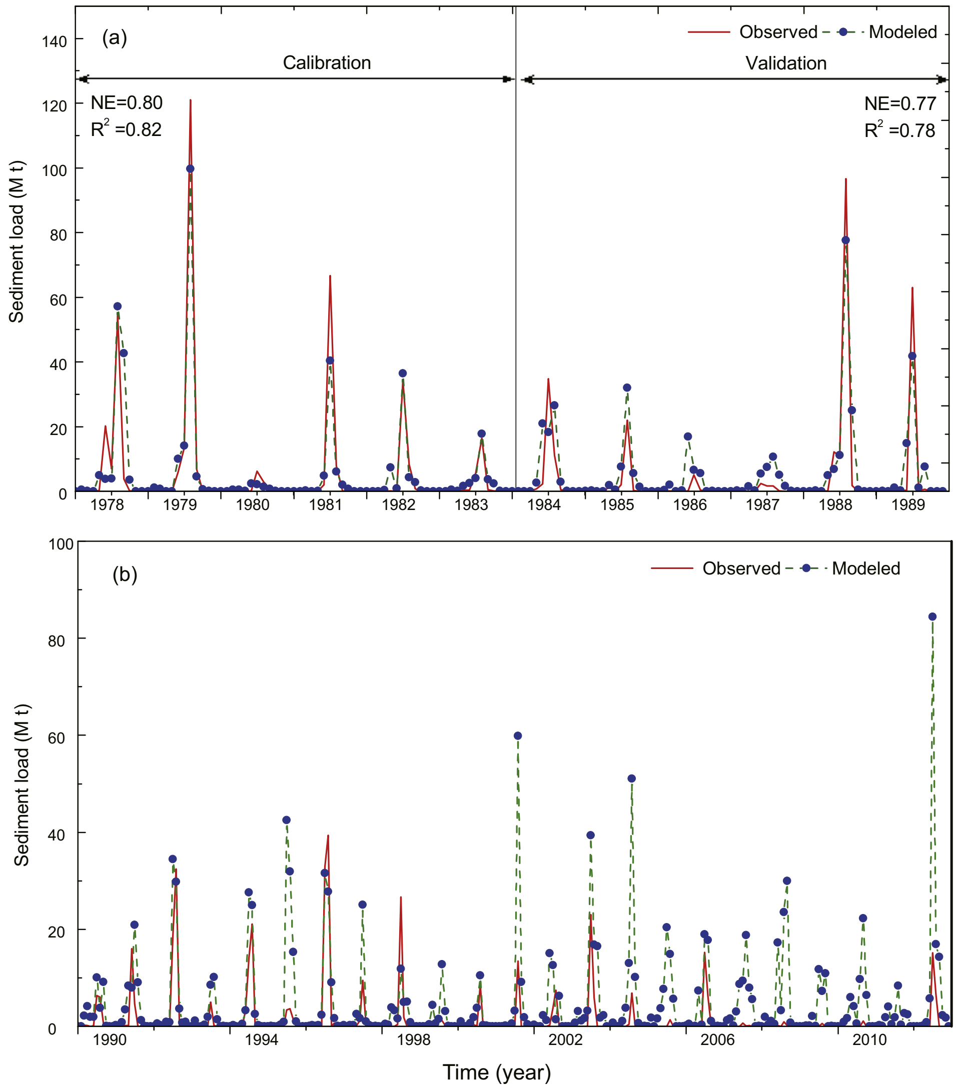

Fig. 9. Monthly sediment load simulated by SWAT model in the Huangfuchuan catchment (a) model calibration and validation from 1978 to1989; (b) observed and simulated monthly sediment load from 1990 to 2012.

reported by Estrada-Carmona et al. (2017), soil erodibility (K factor) was ranked as the third most sensitive factor. Accordingly, their findings were consistent with our results.

Table 1 showed the most sensitive parameters in the SWAT model for sediment load simulation. The most sensitive parameter was the SCS runoff curve number (CN2), followed by the soil erodibility

Table 1
Sensitive parameters adjustment for sediment load simulation in the SWAT model.

Parameter	Description	Ranges	Best fitted value
CN2.mgt	SCS runoff curve number	35–98	14%[a]
ALPHA_BF.gw	Base flow alpha factor	0–1	0.26
GW_DELAY.gw	Groundwater delay	0–500	447
GWQMN.gw	Water depth threshold in the shallow aquifer required for return flow to occur.	0–5000	0.6
GW_REVAP.gw	Groundwater “revap” coefficient.	0.02–0.2	0.14
ESCO.hru	Soil evaporation compensation factor.	0–1	0.76
CANMX.hru	Maximum canopy storage.	0–100	0.09
USLE_C.crop.dat	USLE C factor for land cover	0.01–1	0.15
USLE_K(1).sol	USLE equation soil erodibility (K) factor.	0–0.65	0.58
USLE_P.mgt	USLE equation support practice	0–1	0.99
CH_COV1.rte	Channel erodibility factor.	−0.05–0.6	0.55
CH_COV2.rte	Channel cover factor.	−0.001–1	0.67
CH_S2.rte	Average slope of main channel.	−0.001–10	−7%[a]
CH_L2.rte	Length of main channel.	−0.05–500	29%[a]
SLSUBBSN.hru	Average slope length.	10–150	108%[a]
HRU_SLP.hru	Average slope steepness	0–0.6	128%[a]

[a] Denotes that best fitted values are relative higher/lower than the model default values.

(K) factor (USLE_K), cover management factor (USLE_C), and USLE equation support practice factor (USLE_P). the deep aquifer percolation fraction (RCHRG_DP), the peak rate adjustment factor for sediment routing in the sub-basin (ADJ_PKR), the peak rate adjustment factor for sediment routing in the main channel (PRF), and other parameters. Other sensitive parameters, including slope steepness (HRU_SLP), slope length (SLSUBBSN), main channel slope and channel cover factor are also sensitive parameters affecting sediment yield and transport.

4. Discussion

4.1. Results comparison with different methods

A comparison of the estimated results obtained from six different methods is presented in Fig. 6. All the methods reflect that human activities play a dominant role (93.6 ± 4.1%) in sediment load reduction in the Huangfuchuan catchment. By comparing the estimation with other studies, our findings are generally consistent with their results (Shi and Wang, 2015; Li et al., 2017; Wang et al., 2017). The proportional attributions from various driving factors varied slightly except for linear regression method (Fig. 6). The small discrepancy may be caused by the concepts of the methods, available dataset, geographical conditions, and individual understanding in the driving factors.

As for the simple linear regression and double mass curve method, the relationship between sediment load and rainfall amount were taken into account. Statistical analysis indicated that estimate errors of 13.4% and 8.3% were respectively detected by the linear regression method and double mass curve. The simple linear regression method reconstructed annual sediment load in the changing period by using the equation obtained in the baseline period, the performance of which largely influences the accuracy of its estimation. As shown in Fig. 5, the determination coefficient R^2 for the baseline period was 0.68, which means that only 68% of the variance in observed sediment load can be explained by linear relationship of the equation. Furthermore, other factors (such as potential evapotranspiration, rainfall intensity, frequency, spatial heterogeneity of rainfall in large-scale catchment) were neglected, indeed, having substantial effects on sediment yield (Porto, 2016; Zhang et al., 2005).

The sediment identity factor analysis method took three factors into account, i.e. precipitation, water yield capacity and changes in sediment concentration. Water yield capacity-precipitation and sediment concentration-water yield capacity may be correlated, and this may yield some uncertainty in estimation of individual attribution analysis. The dam-sedimentation based method is also an empirical method based on sediment budget analysis. The results can be considered as a complementary to the double mass curve method.

It has to be noticed that uncertainty exists in spatial variability of sediment yield in the whole catchment, which means that more evenly distributed check dams need to be investigated to obtain the spatial heterogeneity in sedimentation rates. Additionally, uncertainty in sediment volume measurement from the bathymetric survey needs to be concerned. Verstraeten and Poesen (2002) found that the measurement error of bathymetric survey in small ponds is about 20–25%, and an error between 7 and 21% for the calculation of sediment yield from the sedimentation cores.

When comparing the results from different modeling exercises, the SEDD and SWAT models produced relative consistent estimation. Small discrepancy may result from calculation procedures in rainfall erosivity and sediment delivery ratio, which are estimated based on empirical methods in the SEDD model, whereas the SWAT model employed hydrological-process based method for estimation. A comparative analysis of sediment yield simulation was undertaken by Bhattarai and Dutta (2008), which found SEDD model yielded relatively higher values than the observation, whereas the sediment yield was overestimated in the higher rainfall month and underestimated in the lower rainfall month by the MUSLE-based model which SWAT model applied.

4.2. Methods applicability

By comparing the data requirements and calculation procedures, these methods exhibited different merits and limitations for estimation the effects of climate change and human activities on sediment load (Table 2).

Both the linear regression and double mass curve analysis belong to empirical statistical methods, which require least data input and easier to calculate comparing to other methods. A number of studies have successfully applied these methods to separate out the effects of climate change and human activities on sediment load changes (Gao et al., 2017b; Miao et al., 2011; Tang et al., 2013). It seems that these approaches may be suitable for areas with long-term hydro-meteorological observations in relative large-scale regions. However, it should be considered whether the regression equation has good performance to explain the relationship between sediment load and rainfall when determining the applicability of these two methods (Wu et al., 2017). As de Vente et al. (2013) addressed, the empirical statistical methods may be helpful in identify the changes and causes of the sediment load, while they are not ideal for prediction purposes. The sediment identify factor method can be used to determine the effects of different variables on sediment load changes, however, it needs further investigation on the autocorrelation analysis among the factors (Table 2). Furthermore, the method is not applicable to distinguish the relative contribution of individual human activities.

The dam-sedimentation based method is applicable to quantify the trapping effects of dams on sediment load variation. The sedimentation rates in different dam-controlled watersheds are obtainable through field survey. It gives substantial useful information on the quantity of soil loss from hillslope, since the observed sediment load at hydrological stations can only reflect a fraction of the sediment yield in the watershed, which has been strongly influenced by soil and water conservation measures (Kondolf et al., 2014; Zhao et al., 2017).

Soil erosion model is the most complicated approach among these methods. The most promising merit of the soil erosion models is their applicability in different scenarios simulation and future prediction. For example, the SWAT model is usually employed to quantify the effects of climate change, dams operation and land uses changes on sediment load variation (Ma et al., 2014; Ouyang et al., 2018; Zuo et al., 2016), and the results can provide very valuable information for best management practice in river basins.

Data availability and calibration requirements determine a researcher's choice of one model or another. Empirical models and regression equations require generally less input data than spatially distributed models. The model input data is critical to the modeling results, and generate large uncertainties due to both data availability (e.g. climate variables, landscapes, soil conservation measures etc.) and quality (e.g. DEM resolution, accuracy of land use/cover maps etc). More detailed data are necessary to represent the key factors that influence soil erosion processes by avoiding contradictory results. For example, both Li et al. (2017) and Zuo et al. (2016) applied the SWAT model in the same watershed for sediment load simulation, and the differences between their results were largely attributed to the land use information. Therefore, data quality and quantity not only determine the methods selection, but influence the accuracies of the obtained results. Neither SEDD nor SWAT model is processed-based models, which may perform well only if proper calibration and validation were carried out. Bhattarai and Dutta (2008) suggested that the calibration process for these models may be rigorous, since they are data-intensive and require a longer duration of observations and a large number of parameters for calibration. Furthermore, the models required a large number of parameters, which have to be spatially optimized. However, the calibration processes are time consuming and require extensive familiarity

Table 2
Merits and limitations of different methods used in this study.

Methods	Required data	Advantages	Disadvantages
Empirical statistical method	Precipitation, sediment load	Easy to calculate; less data requirements	Lack of physical meaning; uncertainties from regression model
Sediment identity factor	Precipitation, runoff, sediment load	Quantitative analysis for different factors	Potential autocorrelation between variables
Dam-sedimentation based method	Precipitation, sedimentation, dams features, sediment load	Obtaining regional sediment yields	Considerable field surveys, empirical parameters for dams trapping
Erosion models	Precipitation, temperature, humidity, DEM, land-use data, soil data, sediment load, etc.	Different scenarios analysis; includes comprehensive processes	Intensive data required, over-optimization; uncertainties in model verification

with model operation, structure, as well involve the risk of equifinality, where models performed equally and yielded same results with different parameter sets (Beven, 2006; Price et al., 2012). Thus, multi-sources observation data is necessary to obtain or calibrate the model parameters, which can minimize subjectivity and overfitting during the calibration process. It is noted that understanding the type of dominant erosion processes is crucial for the method selection. Most of the models tested are specifically designed to predict sheet, rill erosion, and can therefore not provide information about other processes. Both SEDD and SWAT model need further improvement to consider gully erosion and sediment deposition on hillslope (de Vente et al., 2013).

5. Conclusion

In this study, we applied six different methods to separate the effects of climate change and human activities on sediment load in the Huangfuchuan watershed on the northern Loess Plateau. The main conclusions are summarized as follows:

Consistent results from all the methods indicated that human activities played a dominant role in significant reduction of sediment load in the Huangfuchuan watershed, accounting for $93.6 \pm 4.1\%$ of the total decline, whereas the remaining $6.4 \pm 4.1\%$ of the reduction was attributed to climate change. The sediment load during 1990–2012 exhibited 70.5% reduction compared to that in the baseline period (1955–1989), whereas sediment yields had inconsistent changes with sediment load in the Huangfuchuan watershed. Extremely high soil loss of 149.15 t/ha/a was examined through the check dam sedimentation records, suggesting further needs for soil erosion control in the study area in the future.

Five methods yielded similar estimations of the effects of climate change and human activities on sediment load variation except for the simple linear regression. In comparison, the sediment identify factor method, not used to estimate the effects of human activities, has its own computational characteristic to quantify the attribution of rainfall, water yield capacity, and sediment yield to the changes in sediment load. Dam-sedimentation based method provides good reference for regional sediment yield estimation, but needs considerable field sampling works. Soil erosion modeling is the most complex method with numerous parameters to be calibrated. The model can produce more promising results and reflect the physical processes at different temporal and spatial scales, though require large amount of data input. Both SEDD and SWAT models need further improvement to consider gully erosion and sediment deposition. Thus, researchers and decision makers should keep deep understanding on data requirements, merits and limitations of different methods to choose the most suitable one.

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